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The impact of world oil and food price shocks on the interdependence of Brazil and Russia: SVAR-DCC-GARCH model

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Abstract

This study seeks to identify the extent to which global oil and food price volatilities affected the interdependence of the Brazilian and Russian economies in the period from 1996 to 2021. The ARCH/GARCH framework was used to model the volatility of oil and food prices. The Structural Vector Autoregressive (SVAR) approach was used to ascertain the sensitivity of key economic indicators to oil and food shocks. The Impulse Response Function (IRF) was used to trace short-term effects over a period of 12 months. Subsequently, the multivariate dynamic conditional correlation DCC-GARCH model, created by Engle & Sheppard (2001), was used to model time-varying correlations of paired macroeconomic variables. This study contributes to the empirical literature in two fundamental ways. Firstly, it pairs the two largest oil and food producers in the BRICS bloc. Secondly, unlike some earlier studies, the applied methodology ensures the effectiveness of the results by using stationary time series data. The results show that Brazil and Russia have long-run spillover effects for all macroeconomic variables in response to both oil and food price shocks. Furthermore, money supply and exchange rate variables exhibited declining positive correlation coefficients during the global financial crisis of 2008–2009, but peaked in early 2020 due to the Covid-19 pandemic. As a corollary of the main findings, the researchers recommend that investors should diversify their portfolios beyond these two economies in order to minimize the risk of contagion during severe global crises.

Keywords: oil price volatility, food price volatility, SVAR, IRF, DCC-GARCH, Brazil, Russia, money supply.

JEL: F45, Q02, C32.

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Introduction

The past three decades have been characterized by seemingly more significant than expected swings in energy and agricultural markets worldwide in terms of demand and price. On the downside, energy markets were affected by civil unrest in the oil-rich countries of the Middle East and price wars among top producers. Widespread effects of climate change, such as heat waves, tropical cyclones, severe frosts and droughts, led to a reduction in global food output, while the global population is on the rise, reaching 7,8 billion people in 2021 (World Bank, 2021).

The BRICS countries (Brazil, Russia, India, China and South Africa) are perfectly interwoven into the global energy and agricultural matrix not only as major consumers, but also as major producers. The BRICS countries account for approximately 42% of the world's population (WorldBank, 2021) and therefore present a force to be reckoned with in the trade markets, particularly in light of the trade agreements within the bloc.

Hamilton (2009) finds a strong correlation between the 2008 financial crisis and crude oil prices. Trujillo-Barrera et al. (2012) provide evidence that 10–20% fluctuations in corn and ethanol prices were explained by crude oil price volatility and that this variability increased to 45% during the US financial crisis. This shows that there is a delicate yet strong relationship between energy and food markets, and movements in these markets have a direct bearing on the development of the economy and the economic bloc for that matter.

Brazil. According to the World Bank (2021), the Brazilian population has grown from 167 million in 1997 to 212 million in 2021. Oil consumption peaked in 2014 at 2.7 million barrels per day and gradually decreased to 2.39 million barrels per day in 2019, which is approximately 650% more than the consumption rate of 1965 (BP Statistical Review, 2020). Economic growth slumped between 1998 and 2002, which coincided with the fall in global oil prices. Brazil runs a free-market economy and is rich in natural resources, including forests, rich soils and abundant water supplies. Net FDI inflows were recorded at US$ 2.39 billion in 2010 and rose to US$102.43 in 2011, compared to the meagre $4.86 billion in 1995 (World Bank, 2021). Part of the growth in FDI from 2010 to date can be directly attributed to joining the BRICS union and increased levels of integration with the world's top three emerging markets.

Brazil has significantly reduced energy imports and is the world's second largest producer of ethanol fuel accounting for 24% of global output. Further, the country has a developed hydropower infrastructure due to the abundance of water and it is the world's third largest producer of hydropower. Nuclear power plants have been operating in the country since 1985. According to the BP Statistical Review (2020), Brazil's crude oil production reached a historic level of 2.5 million barrels a day in 2015 and further increased to 2.8 million barrels in 2019. However, this is mostly heavy crude oil, hence the country still needs to import light crude oil. While Brazil's energy production grew by 4.2% in 2015, consumption fell by 1.6% in the same period, representing the first decline since 2009, and this is consistent with falling economic data.

Brazil's productive capacity has allowed it to rise from 16^{th} to 5^{th} position in global food production, turning a new page as a former importer and now a leading exporter of food. The main exports include sugarcane, beef, soybeans, coffee, and orange juice. Brazil is a major world exporter of coarse grain due to its strategic agricultural policy that has contributed to the development of agriculture over the past 30 years. This policy was driven by the need to guarantee food security to the growing population since importing food has become expensive and unsustainable. Agrarian reforms abandoned extensive and intensive methods and pushed for a resource-based concept and sustainable models.

Russia. Russia has a mixed economy following privatization of industry and agriculture in the 1990s and is much less dependent on energy import. According to the World Bank (2021), Russia reported negative annual GDP growth rates in the 1990s, with a slight reprieve in 1997 when the rate was 1.4%. Thereafter, only 1998, 2009, 2015 and 2020 were in the negative and these years correspond to global financial, commodity and health crises. Other BRICS countries also experienced a dip in 2009, but none of them landed in the negative territory. However, Brazil was also in the negative territory in 2015 and 2020 (World Bank, 2021). The 1998 currency crisis was a result of a chronic fiscal deficit due to the war in Chechnya, which coincided with external shocks from the 1997 Asian crisis and falling oil prices. While political stability in other BRICS economies attracts huge amounts of FDI, Russia's case is somewhat different since global investors often want to avoid regions of political uncertainty.

As the largest crude oil exporter in the BRICS bloc, Russia is facing cutbacks in revenue due to depressed oil prices. This can lead to budget cuts, contractionary fiscal policy and massive external borrowing. In 2012, oil and gas accounted for 16% of GDP. Russia has the largest natural gas reserves and the 8th largest oil reserves in the world. Russia's oil production has been on the rise for 7 years, making Russia the world's largest oil exporter in 2015. In 2019, Russia produced 11.5 million barrels of oil per day and consumed 3.32 million barrels per day, which means that approximately 70% of oil was exported (BP Statistical Review, 2020). Much like the drop in consumption in Brazil in 2015, Russia's energy consumption in the same period fell, albeit by a wider margin.

Although Russia dominates the global wheat markets, it recorded, on average, only 5.35% of agricultural value added as a percentage of GDP. This suggests the need to invest in research and development in order to add value to agricultural output and thereby fetch higher prices in the global markets or better yet, use such added value to gain a competitive edge in global markets.

A closer look at Russia's agricultural potential will show that the country has 9% of the earth's arable land, which is certainly an inimitable and unique resource that ought to be harnessed to gain a comparative advantage in the global food market. According to Printseva (2021), Russia has 50% of the planet's black soils, one of the planet's largest freshwater reserves, and 25% of the global forests which, if developed strategically, could eradicate some of the economic woes.

The risks faced by international investors are rising due to high levels of contagion and interdependence among economies, particularly during economic, financial or commodity crises. Globalization, technological advances and deregulation enhance efficiency in global markets, but their flipside is that they tend to breed contagion. Such contagion can rise to toxic levels that can nullify efforts to attain a diversified portfolio in a crisis. Empirical evidence shows that oil and food prices have a profound effect on macroeconomic variables, and particularly those of economic blocs. Brazil and Russia jointly stimulate the world demand and supply of oil and food, hence it is imperative to investigate how these economies respond to price volatility in commodity markets. This study analyses macroeconomic shocks and compares the two economies with respect to high levels of volatility in global oil and food prices. In addition, this research attempts to model the extent to which oil and food price volatilities foster interdependence in order to inform policymakers and global investors.

1. Literature review

There is a plethora of literature covering the issues of oil and food price volatilities (Huang et al., 2005; Cologni & Manera, 2008). There are several schools of thought that seek to explain the effects of world oil and food price volatilities on different economies and economic blocs.

Numerous studies have been conducted to investigate the effect of oil price shocks on macroeconomic variables. One group of scholars explored the theoretical dynamic causal effect of oil on output and inflation (Barro, 1984; Darby, 1982; Burbridge, 1984; Mork, 1989; Hamilton, 1996; Bernanke, 2010). Another group conducted an empirical research on the effect of oil price shocks on a wider range of macroeconomic variables (Hamilton, 2009; Mory, 1993; Cunado & Perez de Garcia, 2003; Lee et al., 2001).

Factors impacting the process of determining global oil prices include geopolitical considerations, market uncertainties, ongoing explorations, growing demand and OPEC decisions (Baffes et al., 2015; Ebrahim et al., 2013; Taghizadeh-Hesary & Yoshino, 2015; Cooper, 2021; Edirington, 2002; Simpson, 2008; Hamilton, 2009). Oil markets have witnessed marked volatility over the past three decades. A dynamic model of rational expectations operates in oil markets where spot prices exceed futures prices when short-term supply is low (Lagi et al., 2011). The forces of supply and demand are often influenced by wars, civil unrest, economic crises, adjustments to trade agreements, and unexpected weather. Since oil production is capital intensive, it is a lot easier to store excess supply for the future than to increase production for immediate consumption. Consequently, this breeds speculation in world oil markets which often fuels price volatility (Lagi et al., 2011; Jiang & Tian, 2005).

Oil often attracts speculators and investors due to its fungibility and ease of storage and transportation compared to other energy commodities. The actions of speculators and investors give a more reliable representation of the future of the global economy. Alquist et al. (2011) argue that investors turn to commodity markets to hedge financial risks and this contributes to rising oil prices due to increased demand.

Several scholars also agree that volatility is a permanent feature of global oil markets since oil exhibits the highest volatility in energy markets (Miklian & Andersen, 2014; Plourde & Watkins, 1998). Furthermore, there is a consensus that oil price volatility has an adverse impact on economic growth and stability, investment, human activity, and national accounts (Miklian & Andersen, 2014; Ramey & Ramey, 1995; Gylfason, 2001; Papyrakis & Gerlagh, 2004; Hamilton, 1983).

Mork (1989) argues that volatility of oil prices matters more than rising price levels because it tends to exacerbate the asymmetrical responses of economic activity. Several researchers confirm the asymmetrical impact of oil price volatility on macroeconomic variables (Federer, 1996; Kuper & Soest, 2006; Rahman & Serletis, 2012; Sadorsky, 1999; Brown & Yucel, 2002; Bredin et al., 2011).

Some scholars agree that oil price volatility negatively affects economic output in the short run, not the long run (Castillo et al., 2010, Baskaya et al., 2013, Guo & Kliesen, 2005; Salim & Rafiq, 2011; Jo, 2012). Furthermore, scholars also agree that investment as well as consumption also fall in response to higher volatility in the world oil markets (Castillo et al., 2010; Elder & Serletis, 2010; Plante & Traum, 2012) — a scenario that is theoretically attributed to higher unemployment as firms try to cut down on production costs (Guo & Kliesen, 2005; Rafiq et al., 2009).

In-depth studies have been conducted to explore the macroeconomic effects of oil price volatility on various economies (Burbridge, 1984; Mork, 1989; Mork et al., 1994; Lee et al., 2001; Khan & Ahmed, 2011; Hamilton, 2009; Uri, 1996; Jo, 2012; Salim & Rafiq, 2011). Guo & Kliesen (2005) studied the effect of oil price volatility on the US economy from 1984 to 1994 using Granger Causality Tests and found that daily volatility of oil futures was inversely related to future GDP. Yang et al. (2012) assessed the Chinese economy and found that oil price volatility Granger caused movements in GDP growth rate, consumer price level and monetary policy, and that economic growth rates Granger caused the price level.

Hamilton (2009) observes that the dramatic drop in world oil prices in 2008 led to a drop in economic production in the USA, which, in turn, prompted retrenchment of employees in various industries. Household incomes declined drastically, leading to defaults on mortgages and subsequent foreclosures and bank failures as the crises escalated. The rise in oil prices in 2012 pushed the US CPI upward, while depressing factory output. Blanchard & Gali (2007) compared the response of US GDP and CPI to the oil price shocks of the 1970s and 2000s and found that the oil shocks were among a number of shocks of different origins and that oil shocks had lower macroeconomic effects in the 2000s than in the 1970s. Evidence from Norway shows that Norway's GDP fluctuates depending on oil prices, it fell from €50 billion in 2008 to less than €35 billion in 2009 (Miklian & Andersen, 2014). This cements the theory that oil volatility and GDP have an inverse relationship.

Khan & Ahmed (2011) used the SVAR approach and found that Pakistan's economy was in stagflation due to supply-side shocks from global oil prices. Amjad et al. (2011) also conclude that the supply shocks increased inflation while economic growth was declining, leading to high unemployment rates and poverty in Pakistan. In a study conducted by Baffes et al. (2015), oil price volatility is linked to volatility in foreign exchange markets as well as equity markets. The authors provided evidence of capital outflows from oil-exporting countries in 2014, leading to sharp depreciation of currencies in Russia, Venezuela, Colombia, Nigeria and Angola due to a sharp decrease in oil prices. Oil price volatility adversely affects both oil-exporting and oil-importing economies, with the latter being more disadvantaged than the former.

Using ARCH/GARCH, Baffes et al. (2015) found that oil price volatility was higher between 2011 and 2014 than in prior periods. Taghizadeh-Hesary & Yoshino (2015) used the SVAR model to analyze the effects of oil price volatility on two groups: the developed US and Japan versus emerging China. They found that GDP growth rates of the latter were more susceptible to oil price fluctuations than of the former, yet the inflation response of China was found to be milder than that of the US and Japan. China's low inflation rate was attributed to higher economic growth rates which shift the aggregate supply curve to the right, thereby mitigating a rise in the price level.

According to the Commonwealth Scientific and Industrial Research Organization (CSIRO), there has been a 77% increase in food imports over the past five decades, which indicates that the global village is becoming increasingly interdependent. Over the past decade, grain prices have risen significantly due to unfavourable weather conditions as well as increasing demand for biofuels as governments push for alternative energy sources. Wright (2011) and Gilbert & Morgan (2011) concur that low stock levels amplify grain price volatility. These authors found that the 2007–2008 price hikes were the result of low storage levels after the diversion of large volumes of grains and oilseeds to biofuels production without allowing enough time to build stocks through new high yield varieties. Thus, Gilbert & Morgan (2011) conclude that volatility will remain high in the medium term until productivity increases.

Several causes of rising food prices have been documented by economists. Gilbert (2010) claims that high food prices in the 2000s were driven by rapid economic growth in Asia, while the World Bank attributed the increase in prices to underinvestment in agriculture. Wright (2011) and Mitchell (2008) identify the prolonged Australian droughts of 2006–2007 and poor harvests in Europe in 2007 as contributing factors, while Abbott et al. (2008) conclude that the depreciating US dollar is the key driver of rising food prices.

The unpredictable variability of food prices is attributed to production shocks caused mainly by unfavorable weather and demand shocks derived from incomes and policy changes (Gilbert, 2006; Christiaensen, 2009; Hajkowicz et al., 2012). There is a general consensus that global warming will continue to adversely affect agricultural output in the long run, which means that part of the increase in food price volatility experienced over the past two decades is actually permanent. Gilbert & Morgan (2011) note that episodes of high volatility in food prices are short-lived and often followed by lengthy periods of stability, which implies that the 2008 price spike may not necessarily be a recurring event in the near future. Studies such as Bloch et al. (2007) demonstrate that global food price volatility has a direct effect on consumer price inflation and it often prompts demands for higher wages. However, some scholars argue that this link is getting weaker in developed countries due to advanced derivative markets and crop insurance (Gilbert & Morgan, 2011; Moschini & Hennessy, 2001).

In their study, Ridler & Yandle (1972) conclude that since most commodity prices are quoted in US dollars, the exchange rate variability of the USD will feed into that of world oil and food prices. Furthermore, the variability of the local currency against the USD will also fuel volatility. Numerous strategies are being adopted by governments to curb imported food price volatility and one of them entails the use of buffer stocks. Miranda & Helmberger (1988) study the effect of government intervention on the US soybean market and find that food programs lead to price stabilization in the long run but also crowd out the private sector. Salant (1983) shows that public stockholding perpetuates speculation, particularly in landlocked countries with limited access to world markets.

Recent studies show that the quest for alternative sources of energy necessitated by rising oil prices has driven major economies, such as the USA, to divert food stocks to biofuel production (Gilbert & Morgan, 2011; Baffes, 2007; Mitchell, 2008). Brazil has an upper hand in this regard as ethanol fuel produced from sugar yields more energy than that derived from corn, the US option. Some researchers agree that oil and food price volatility has an adverse effect on the rate of world economic growth (Headey & Fan, 2008; Abbott et al., 2009; Galesi & Lombardi, 2009). Volatile food prices increase import bills of food-importing countries, which can lead to trade deficits and an unfavourable balance of payments in the long run. Further, rising food prices may increase the demand for money and raise interest rates, which will lead to unfavourable exchange rates. It was against this background that the researchers opted to study the effects of oil and food price volatility on output, inflation, money supply, interest rates, and exchange rates.

2. Materials and methods

This study uses a systematic approach to data collection, analysis, and presentation. The researchers adopted a non-interventionist theoretical approach anchored on time series of observed data on several variables in order to draw conclusions after their thorough analysis. The same research design was adopted by a number of scholars who studied the interdependence among economies using historical time series data (Engle, 1982; Patton, 2006; Silvennoinen & Thorp, 2009). The study covers the period from October 1996 to March 2021, inclusive. Firstly, volatilities of global oil and food prices were measured, then oil and food price shocks for five key macroeconomic variables were computed and analyzed using the Structural Vector Autoregressive Approach (SVAR). After that, the Impulse Response Functions (IRF) were computed for a period of 12 months. In an attempt to completely capture the effects of innovations related to oil and food, the residuals of the SVAR were analyzed using a DCC-GARCH model which allowed to compare the levels of interdependence during volatile and calm periods.

2.1. Autoregressive conditional heteroskedasticity (ARCH/GARCH) models

The dynamic nature of economic time series data has been at the center of academic studies for several decades. Volatility is a phenomenon of wide swings found in time series data (Gujarati, 2004; Brooks, 2008). The ARCH family of models was pioneered by Engle (1982) and this approach involves the calculation of standard deviations of log ratios of time lags. This model attempts to incorporate the heteroscedasticity observed at different periods in a time series. The ARCH and GARCH models are not aimed at correcting heteroscedasticity but at modelling it and predicting variation for each term (Engle et al., 1990). Bollerslev (1986) develops this idea further by introducing declining weights for older data that are asymptotic to zero. Bollerslev (1986) argues in favor of a model that distinguishes between predictable and unpredictable components but also allows for the variance of an unpredictable component using a generalized autoregressive conditional heteroscedasticity model (GARCH).

According to Engle (2001), the GARCH model has the following form:

$$h_{t+1} = \omega + \alpha(r_i - m_t)^2 + \beta h_t = \omega + \alpha_i h_t \varepsilon_t^2 + \beta h_{t'}, \tag{1}$$

where: h_t is the variance of the residuals of regression, $r_t = m_t + \sqrt{h_t}\ \varepsilon_{t'}$;
ω, α and β are positive constants to be estimated;
the weights are $(1 - \alpha - \beta, \beta, \alpha$;
long-run variance is $\sqrt{\omega / (1 - \alpha - \beta)}$, where $|\alpha + \beta < 1|$.

When the volatility graphs were produced, periods of high volatility were identified for comparison with correlation coefficients in the DCC-GARCH results.

2.2. Structural vector auto-regressive models and impulse response functions

The SVAR approach requires that the data in the time series be stationary at the same level in order to avoid spurious results. The Augmented Dickey-Fuller (ADF) test for stationarity was developed by Dickey and Fuller in 1979. The ADF is a unit root test with a null hypothesis that states that a series has a unit root, which means that it is non-stationary.

The nature of this study required that we selected the most appropriate lag length to obtain the best model. The Akaike Information Criterion (AIC) compares different econometric models on the basis of the information lost when using a particular model. This approach was developed by H. Akaike in 1974 (Akaike, 1974). The Bayesian information criterion (BIC) imposes stricter penalties to avoid overfitting and is more preferred by researchers, especially in studies with large samples (Koehler & Murphree, 1988). The Hannan-Quinn information criterion (HQIC) imposes a penalty for adding more regressors to the model in an attempt to minimize the value of the residual sum of squares (Hannan & Quinn, 1979).

Four SVAR models were developed, two for each economy, one with oil as the exogenous variable and another with food. Vector autoregressive (VAR) models are used to model simultaneous equations whereby each endogenous variable is explained by its lag values, as well as lagged values of other endogenous variables under study (Gujarati, 2004). One of the major drawbacks of VAR is that it disregards information about specific drivers of each variable assuming symmetrical effects in a structural sense. As such, the Structural VAR (SVAR) was developed by Professor Sims in 1980 to allow for each variable to be independently affected by the exogenous variable as is often the case in economics. SVAR allows the researcher to identify unexpected structural effects of one variable on other variables and determine which variables are exogenous and which are endogenous, based on economic theory (Chuku et al., 2011; Khan & Ahmed, 2011; Leeper et al., 1996). Further, SVAR caters for short-run effects of variables on each other, rather than immediate effects as implied by VAR. As such, this model is preferred and often followed by the impulse response function (IRF) that models the transmission of shocks in the short run (Khan & Ahmed, 2011; Kim, 2005). The model assumes that structural shocks are not correlated, which is supported by economic theory. If an error term (impulse or shock) changes by 1 standard deviation, it will trigger a change in the exogenous variable of this particular equation, but since there are endogenous variables in this regression equation, they will also change. The impulse response functions capture the snowball effect of the error term on all variables in the given equation (Gujarati, 2004). The generalized impulse response function (IRF) fully accounts for the historical patterns of correlations observed amongst different shocks (Koop et al., 1996).

The key stage in the SVAR model is identification. We needed to identify matrix A in the SVAR equation below:

$$AX_t = A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_p X_{t-p} + \varepsilon_t, \tag{2}$$

where: X_t is *a* (n x 1) vector of endogenous variables [$X_t = (o^*_t, fi^*_t, y_t, p_t, m_t, i_t, e_t)$] that is oil (or food — fo^*_t) price, federal funds rate, output, consumer price inflation, money supply, short-term interest rate, and real effective exchange rates, respectively;

A is an invertible (n x n) matrix of coefficients of endogenous variables;

A_i's are (n x n) matrices that show the dynamic relationships among all the k variables;

ε_t is an (n x 1) vector of structural error terms;

p is the number of time lags.

Kim and Roubini (1999) introduce a robust model that includes the effect of the US Federal Funds Rate on the exchange rates of the G6 economies. However, Brischetto and Voss (1999) adopt the model of Cushman and Zha (1997) which captures the effect of federal rates on domestic interest rates, arguing that it presents more realistic results since federal funds rates are an indicator of oil inflation as oil prices are given in US dollars.

The SVAR model for global oil prices is structured as follows (Brischetto & Voss, 1999):

$$A_0 x_t = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -a^0_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ -a^0_{31} & 0 & 1 & 0 & 0 & 0 & 0 \\ -a^0_{41} & 0 & -a^0_{43} & 1 & 0 & 0 & 0 \\ 0 & 0 & -a^0_{53} & -a^0_{54} & 1 & -a^0_{56} & 0 \\ -a^0_{61} & -a^0_{62} & 0 & 0 & -a^0_{65} & 1 & -a^0_{67} \\ -a^0_{71} & -a^0_{72} & -a^0_{73} & -a^0_{74} & -a^0_{75} & -a^0_{76} & 1 \end{pmatrix} \begin{pmatrix} o^*_t \\ fi^*_t \\ y_t \\ p_t \\ m_t \\ i_t \\ e_t \end{pmatrix} \tag{3}$$

The Lagrange Multiplier (LM) test for ARCH was developed by Engle in 1982 and is used to determine the validity of SVAR restrictions since the model was over-identified. The null hypothesis states that the error terms of the SVAR models are homoscedastic and the null hypothesis is rejected when the *p-value* exceeds 5%.

Further, the Jarque-Bera test for normality was developed by C. Jarque and A. K. Bera in 1980. This test was employed to test the residuals for normality to authenticate the SVAR model. An Autoregressive (AR) model that captures the appropriate lag length is expected to capture all the variability that is explained by its lags, so that the error terms are independent. The test measures the skewness and kurtosis with the null hypothesis that a variable follows the normal distribution.

2.3. Dynamic Conditional Correlation (DCC-GARCH)

Various scientists have developed several approaches to multivariate GARCH models for calculating the correlation matrix. Bollerslev (1990) developed a constant conditional correlation estimator in which the conditional correlation matrix R was constant. Engle (2002) modified Bollerslev's work and proposed a dynamic conditional correlation (DCC) model in which R varied with time, which is often the case in economic and financial data series. The Dynamic Conditional Correlation (DCC-GARCH) model was used by several scholars to assess contagion (Chao & Parhizgani, 2008; Bonga-Bonga, 2015). The DCC-GARCH model incorporates univariate GARCH models with parsimonious parametric models in order to model time-varying correlations. This model is often preferred because it is nonlinear in nature (Engle, 2002). By avoiding the complexity of multivariate GARCH models, the DCC-GARCH directly parameterizes conditional correlations, which simplifies computation since the number of parameters does not depend on the number of time series to be correlated. This advantage allows for large correlation matrices to be studied and helps to model the asymmetric effects of exogenous variables on several endogenous ones. Engle and Sheppard (2001) specified the DCC-GARCH model as follows:

$$r_t \mid \zeta_{t-1} \sim N(0, D_t R_t D_t), \tag{4}$$

where: $D^2_t = \text{diag}\{w_i\} + \text{diag}\{k_i\} \circ r_{t-1} r'_{t-1} + \text{diag}\{\lambda_i\} \circ D^2_{t-1}$;

$\varepsilon_t = D_t^{-1} r_t$;

$R_t = \text{diag}\{Q_t\}^{-1} Q_t \text{ diag } \{Q_t\}^{-1}$;

where R_t is the correlation matrix containing the conditional correlations;

the k x k symmetric positive definite matrix Q_t is given by:

$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \eta_{t-1} \eta'_{t-1} + \theta_2 Q_{t-1}$;

where θ_1 and θ_2 are non-negative scalar parameters that capture the effects of previous shocks and previous dynamic conditional correlation, respectively (Chang et al., 2011).

According to Bonga-Bonga (2015), the residuals of the SVAR model were the input of the DCC-GARCH model. The output graphs of the DCC-GARCH were compared to the volatility graphs of global oil and food prices in order to identify the behavior of correlations during periods of high volatility and volatility clustering.

3. Data sources

All data was extracted from the Federal Reserve Bank of St. Louis and cited accordingly. Monthly time series data from October 1996 to March 2021 were used. The variables in this study can be grouped into 2 categories, namely international and domestic. The international variables are world oil and food prices. The domestic variables are industrial output, inflation rate, money supply, nominal interest rates, and real effective exchange rates.

World oil prices (o_t) were proxied by the West Texas Intermediate (WTI) monthly spot price in US dollars. The WTI is the most preferred source because it represents trade in the advanced and efficient US oil markets. World food prices (fo_t) were proxied by the Global Price of Food Index, the average monthly price in nominal USD with 2016 as the base year. Production Total Industry (PTI) was measured by the total industry production (y_t) in each country, which is indicative of the productive activities of economic agents. Inflation (p_t) was proxied by CPI which is expressed as an index of base year 2010 for both countries. Inflation is important for this study because an oil shock often manifests in the growth of consumer prices, hence the need to model the impact of oil shocks on each economy's level of inflation. Whenever monetary authorities anticipate an oil shock, they tend to adjust the level of money supply (m_t) in the economy in order to safeguard the local economy from the shock. These interventionist activities often involve the use of short-term interest rates and money supply to achieve the desired goal. Therefore, an immediate 24-hour call money (interbank) rate was used to represent short-term interest rates (i_t). Annualized rates were used since they are always expressed as a percentage. The US federal funds rate was represented by (fi_t). The reciprocal of the exchange rates (e_t) of each of the BRICS currencies against the USD was taken to represent the real effective exchange rates. All data were converted into natural logarithms, except interest rates and the federal funds rate, in order to standardize the unit of measurement.

4. Results

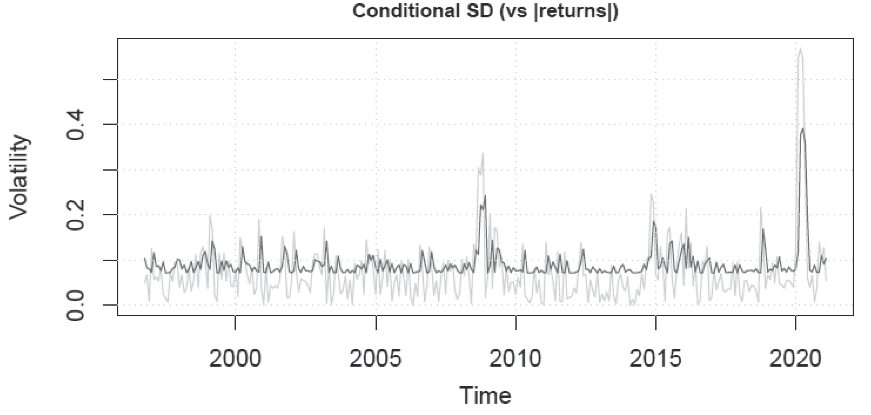
This section presents the results in chronological order, starting with the ARCH/GARCH models followed by the SVAR and IRF models and ending with the DCC-GARCH results. The ADF test results showed that all the time series used had a unit root meaning that they were not stationary. Upon first differencing, the data was found to be stationary, hence it was analyzed as such.

3.1. ARCH/GARCH volatility models

Volatility of world oil prices. From 1996 to 2007, most of the volatility was explained by geopolitical crises in the Middle East and the failure to increase production to match the growing global demand. The three periods of marked volatility are the global financial crisis of 2008–2009, the commodity crisis of 2014, and the onset of the Covid-19 pandemic in early 2020. Figure 1 models the volatility of world oil prices from October 1996 to March 2021. The equation is given by:

$$h_{t+1} = 0.005 + 0.431h_t\varepsilon_t^2 + 0.000h_{t'}, \tag{5}$$

which means that only the ARCH term was found to be significant.



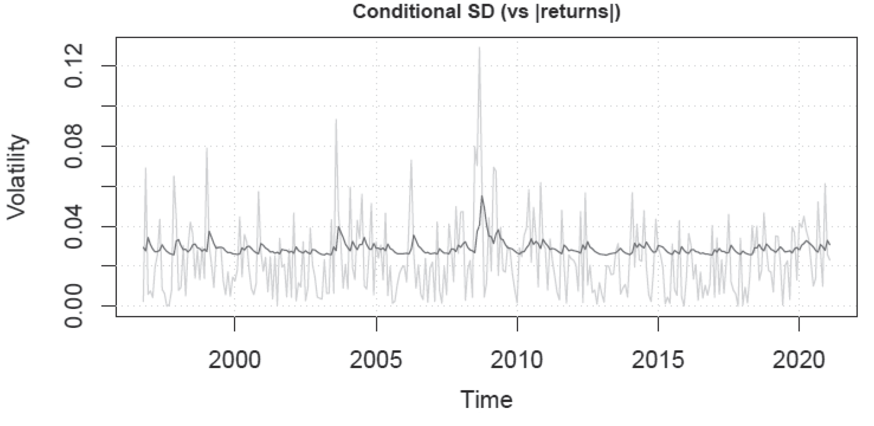
Source: calculated by the authors.

Figure 1. Volatility of world oil prices

Volatility of world food prices. As seen in Figure 2, world food prices exhibited relatively low volatility prior to the global financial crisis of 2008–2009. There is one prolonged period of high volatility – from 1st quarter of 2008 to 2nd quarter of 2010. The equation is given by:

$$h_{t+1} = 0.0002 + 0.089h_t\varepsilon_t^2 + 0.64h_{t'.} \tag{6}$$

However, only the GARCH term with a *p-value* below 0.05 is significant.



Source: calculated by the authors.

Figure 2. Volatility of world food prices

Dynamic conditional correlations of economic time series were analyzed based on the periods of excessive volatility in order to assess whether oil and food price volatility influences the levels of interdependence of the two economies.

3.2. SVAR and IRF models

The structural vector autoregressive model is used to isolate contemporaneous relations between two or more variables. According to the results of the Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan-Quinn information criterion (HQIC), the Brazilian models were estimated with one lag, while the Russian ones were estimated using four lags. Two separate matrices were developed for each country to measure the impact of oil and food shocks, respectively, in order to isolate the direct impact of each exogenous variable. The p-values of the (LM) ARCH and the Jacque-Bera normality tests were below 5% for all SVARs, which indicates that the residuals of the SVARs are homoscedastic and follow a normal distribution, respectively.

Brazil's SVAR and IRF oil model. The structural coefficients for the Brazilian oil model are given below.

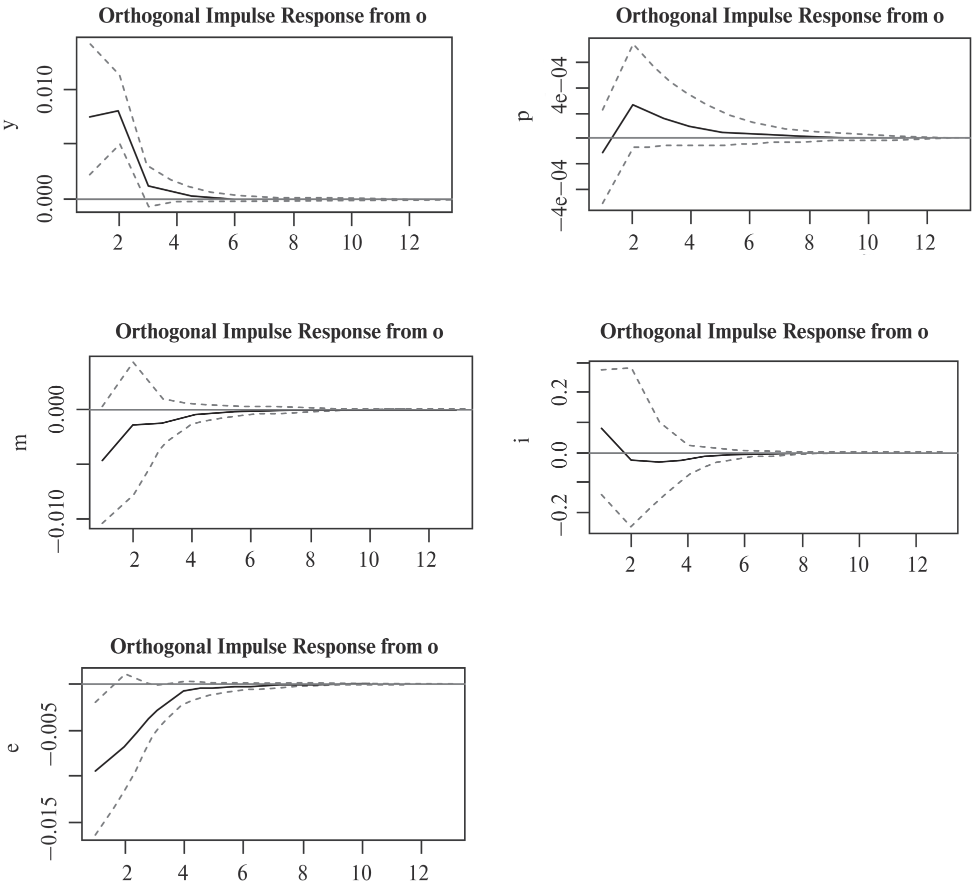
Table 1. $A_o x_t$ Matrix Oil — Brazil

o_t^*	fi_t^*	y_t	p_t	m_t	i_t	e_t
1						
–2.665 (0.220)	1					
–0.198 (0.029)	0	1				
0.004 (0.002)	0	–0.016 (0.008)	1			
0	0	–40.92 (305.6)	2.53 (3020)	1	–76.47 –	
0.088 (25.226)	0.217 (19.594)	0 (0.000)	0 (0.000)	–387.5 –	1	1070 –
–6.004 (2.158)	1.648 (2.585)	2.011 (14.75)	18.40 (102.6)	–91.00 –	–0.049 (0.151)	1

Note: LR Overidentification Test χ^2 (4) 785 (2e-16).

Source: calculated by the authors.

The results presented in Table 1 show that oil has a negative impact on output, which differs from the findings of Brischetto and Voss (1999) who used the same model for Australia, a net importer of oil. However, the results are similar to the findings of Kim and Roubini (1999) for the United Kingdom and France. The impact of oil on inflation and interest rates is positive for Canada, as found by Kim and Roubini (1999), Brischetto and Voss (1999) in the Australian model, and Khan and Ahmed (2011) in the Pakistani model. The effect of oil on exchange rates is negative in line with the finding of Kim and Roubini (1999) in their German, Japanese and French models.



Source: calculated by the authors.

Figure 3. Impulse response functions for the Brazilian oil model

The orthogonal impulse function for the Brazilian model (Figure 3) shows short-lived effects because the model was estimated with only one lag. In response to oil shocks, output rises, prices also increase, money supply falls, interest rates move upward slightly. However, they all revert back to the pre-shock levels within 6 months.

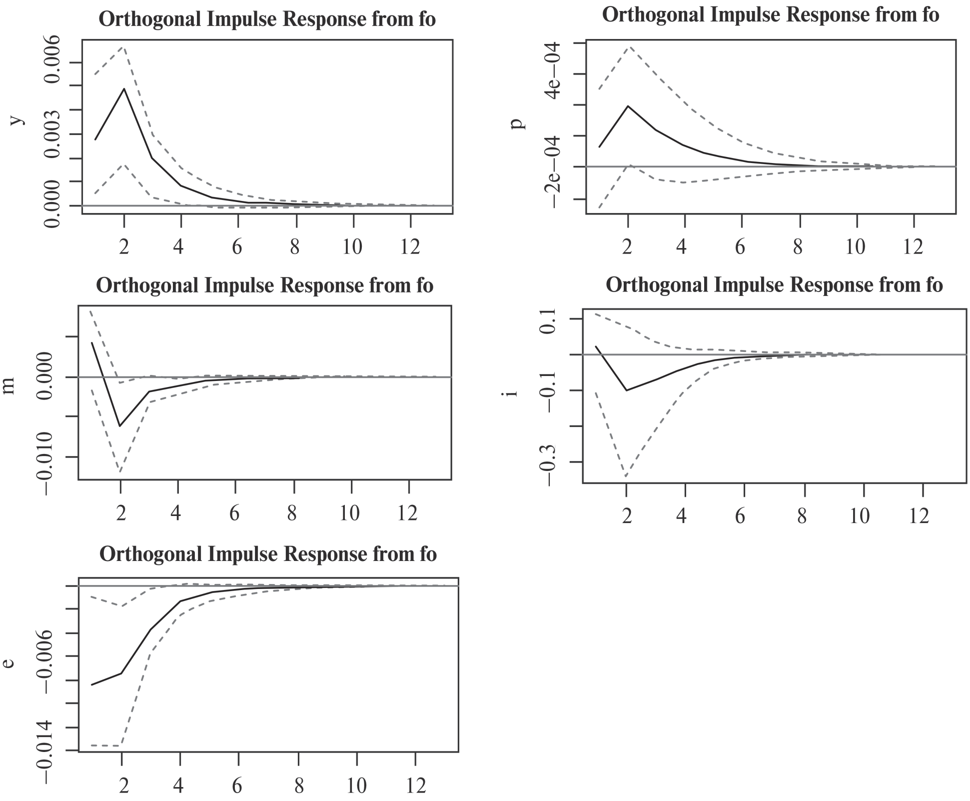
Brazil's SVAR and IRF food model. The Brazilian SVAR food model was estimated as follows.

Table 2. $A_o x_t$ Matrix Food — Brazil

fo_t^*	fi_t^*	y_t	p_t	m_t	i_t	e_t
1						
−0.826 (0.266)	1					
−0.113 (0.050)	0	1				
−0.004 (0.006)	0	−0.014 (0.007)	1			
0	0	−11.43 (150.1)	0.873 (1865.9)	1	−59.45 –	
2.935 (207.7)	15.48 (43.54)	0	0	87.33 (112.2)	1	2087 –
71.66 –	3.028 (6.328)	−25.17 (29.24)	12.00 (207.8)	−257.43 –	−0.413 (0.286)	1

Note: LR Overidentification Test χ^2 (4) 15 (0.005).

Source: calculated by the authors.



Source: calculated by the authors.

Figure 4. Impulse response functions for the Brazilian food model

Figure 4 shows the orthogonal impulse response of output to world food prices. It is evident that innovations in the field of food are immediately felt with a rise in output and inflation, a fall in money supply and interest rates, and an appreciation of the local currency against the USD.

Russia's SVAR and IRF oil model. Contemporaneous structural coefficients were calculated as follows.

Table 3. $A_o x_t$ Matrix Oil — Russia

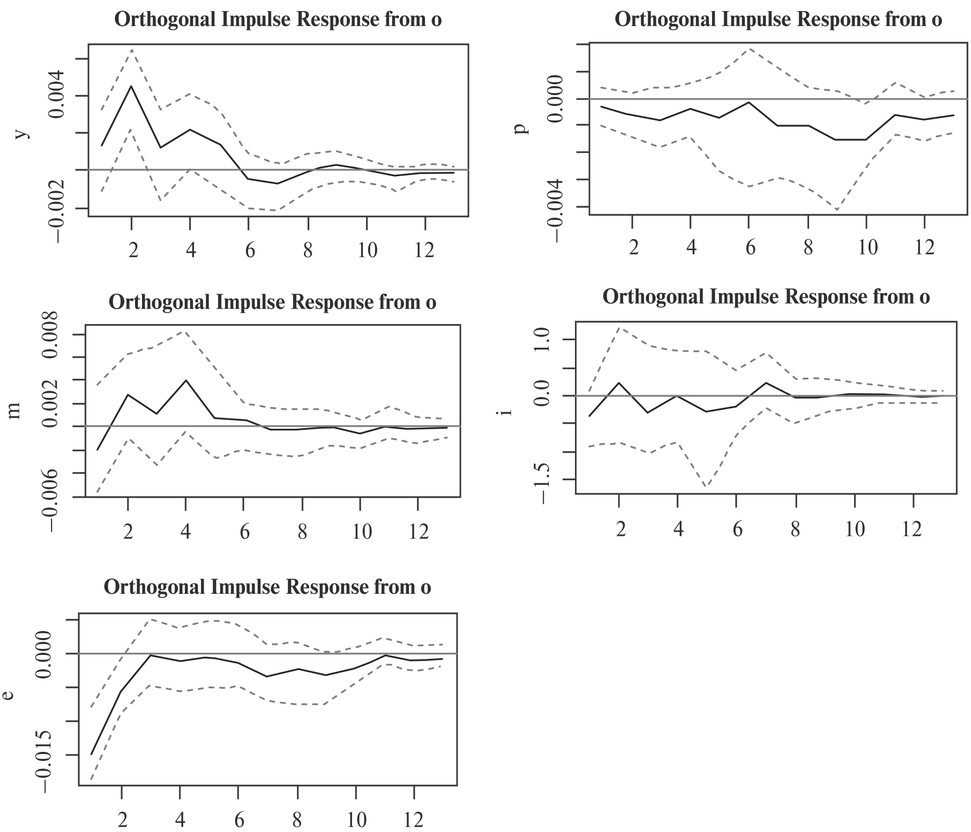
o_t^*	fi_t^*	y_t	p_t	m_t	i_t	e_t
1						
–0.434 (0.077)	1					
–0.014 (0.011)	0	1				
0.003 (0.004)	0	0.016 (0.021)	1			
0	0	–0.389 (0.123)	0.263 (0.371)	1	0.000 (0.001)	
–1.329 (10.47)	–0.914 (3.820)	0	0	–3.825 (25.28)	1	–60.51 (67.33)
0.156 (0.024)	–0.004 (0.016)	0.110 (0.110)	–2.108 (0.401)	0.009 (0.060)	0.001 (0.001)	1

Note: LR Overidentification Test χ^2 (4) 46 (2e-09).

Source: calculated by the authors.

As in the Brazilian model, Table 3 shows that oil has a negative impact on output, which contradicts the findings of Javid and Munir (2010) who found a positive coefficient. It also shows a positive effect on prices, as in the work by Kim and Roubini (1999) who reported about a positive effect of oil price innovations on the Canadian Consumer Price Index. Oil shocks have a positive effect on exchange rates, which differs from the results of Javid and Munir (2010) for Pakistan. Oil has a negative effect on interest rates – a finding which contradicts Javid and Munir (2010) and Brischetto and Voss (1999). However, Kim and Roubini (1999) found a negative effect for Germany, Japan and France.

The orthogonal impulse response to world oil shocks tends to last longer in Russia than in Brazil, probably, because up to four lags were necessary to estimate an efficient SVAR model. The graphs in Figure 5 indicate that macroeconomic variables follow a path of marked volatility as they revert to pre-shock levels, hence it takes longer for them to settle. Output, money supply and interest rates are rising in response to innovations in the oil market, while inflation is declining and the Ruble is appreciating.



Source: calculated by the authors.

Figure 5. Impulse response functions for the Russian oil model

Russia's SVAR and IRF food model. The Russian SVAR food model was computed as follows.

Table 4. $A_o x_t$ Matrix Food — Russia

fo_t^*	fi_t^*	y_t	p_t	m_t	i_t	e_t
1						
−0.802 (0.270)	1					
−0.218 (0.038)	0	1				
0.054 (0.013)	0	−0.024 (0.020)	1			
0	0	−0.266 (0.117)	−0.254 (0.356)	1	0.000 -	

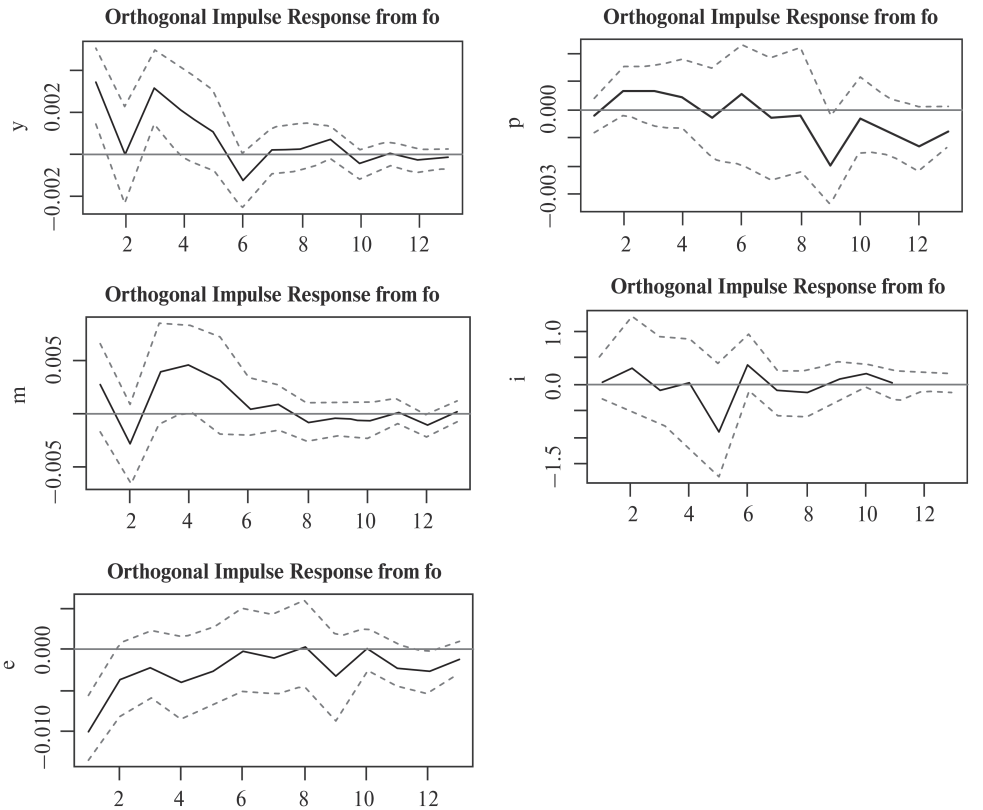
Table 4. Continued

fo_t^*	fi_t^*	y_t	p_t	m_t	i_t	e_t
0.093 (170.35)	0.095 (36.78)	0	0	−7.380 –	1	−32.47 –
0.728 (0.109)	0.051 (0.021)	0.332 (0.152)	−1.663 (0.440)	0.222 (0.077)	0.002 –	1

Note: LR Overidentification Test χ^2 (4) 1501 (2e-16).

Source: calculated by the authors.

Table 4 presents the food matrix for Russia. In contrast to the findings of Khan and Ahmed (2011), food shocks have a positive effect on inflation mainly because Russia is a major exporter of food and Pakistan is a net importer. World food prices seem to have a negative effect on output, driving industrial production down, since agriculture accounts for a significant portion of economic activity in Russia. Further, food prices have a positive effect on interest rates and exchange rates for the same reason.



Source: calculated by the authors.

Figure 6. Impulse response functions for the Russian food model

As can be seen from Figure 6, impulse responses exhibit rugged movements, sometimes crossing from negative to positive territory after food price innovations. Initially, output, inflation and interest rates respond by rising, while the foreign exchange appreciates against the USD. Thereafter, all variables experience alternating periods of ups and downs before arriving at the pre-shock levels. Inflation, money supply and the foreign exchange rate tend to take longer to return to the pre-shock readings.

3.3. DCC-GARCH models

DCC-GARCH oil model. DCC-GARCH computations employed for measuring the spillover effects from Russia to Brazil (and vice versa) using the residuals of the SVAR oil models yielded the following p-values.

Table 5. DCC-GARCH oil model

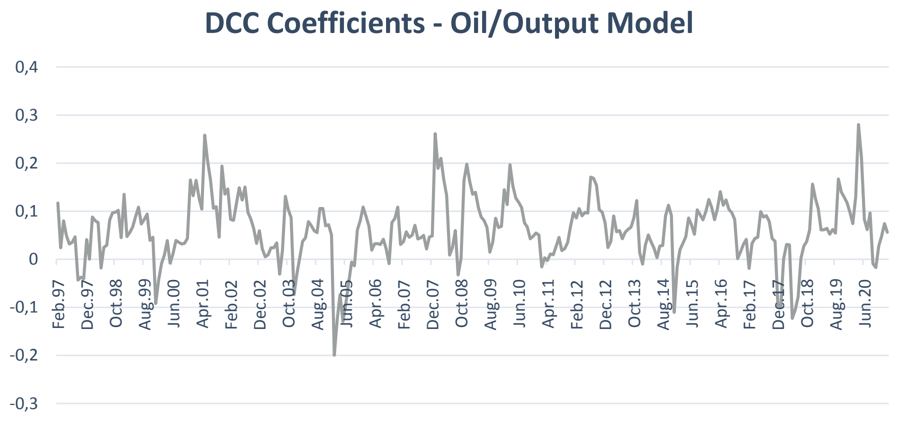
	Output (y)	*Inflation (p)*	*Money supply (m)*	*Interest rates (i)*	*Exchange rate (e)*
dcca1 (short-run)	0.467	0.998	0.007	0.999	0.004
dccb1 (long-run)	0.040	0.000	0.000	0.001	0.000

Source: calculated by the authors.

As shown in Table 5, only long-term spillover effects are significant for output, inflation and interest rates. Money supply and exhange rate are characterized by both short-term and long-term spillover effects, which means there is a higher risk of contagion in an oil or food crisis. The plot of dynamic correlations for output shows that the highest possible positive correlation is 0.3, which is a fairly low correlation. However, correlations for money supply and exchange rates are strong enough to perpetuate contagion in a crisis.

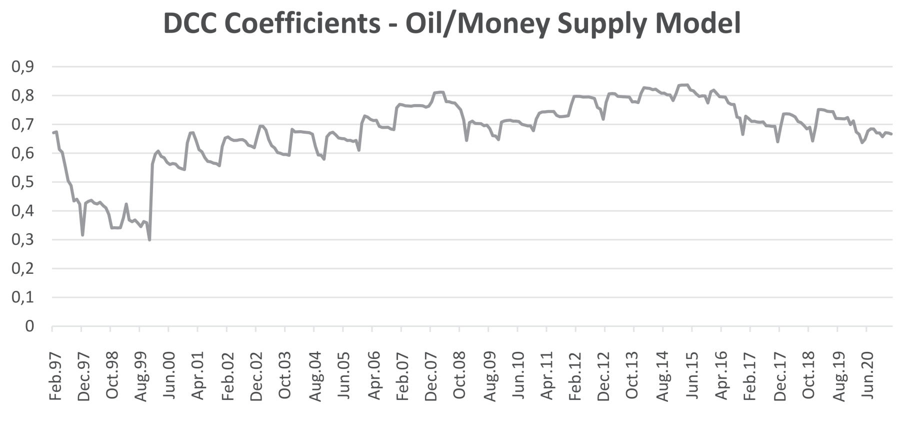
The peaks of output are far greater than those of oil volatility, and in most cases when they coincide, correlations seem to over-compensate for the oil volatility, which indicates that there are other factors that influence the interdependence. In early 2020, output recorded the highest dynamic correlation coefficient during the onset of the Covid-19 pandemic when oil price volatility also shot up. However, in 2018 and during the commodity crisis of 2014–2015, the correlations were negative. During the global financial crisis of 2008–2009, the second highest positive correlation was observed, albeit below 0.3. The third highest positive correlation was reported in mid-2001, but the volatility of oil was mild. The BRIC was formed in 2009, but there is no significant shift in time-varying correlations from that time to date.

The results in Figure 7 show that correlations range between 0.15 and 0.16, which can be easily diversified by a prudent investor. Similarly, the time-varying correlations for interest rates are negligible ranging from 0.02 to 0.03. There are three significant peaks in the positive region, namely early 2001, late 2007, and early 2020. One significant dip occurred in early 2005 and amounted to -0.2.



Source: calculated by the authors.

Figure 7. Time-varying correlations for oil – output model

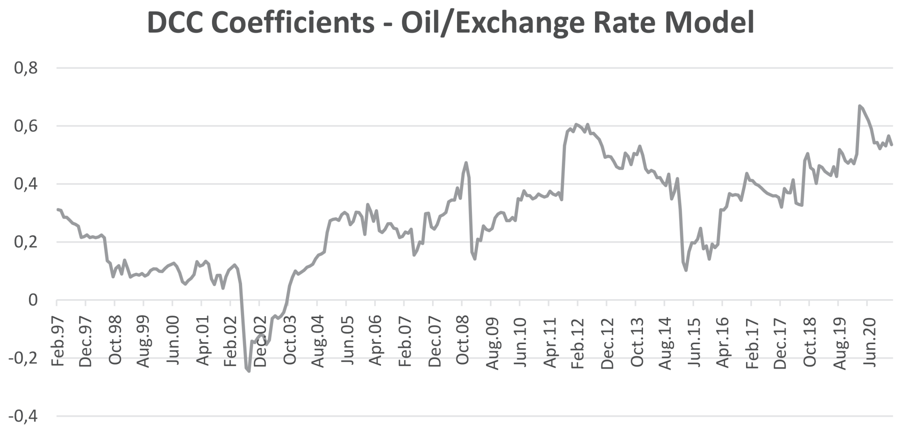


Source: calculated by the authors.

Figure 8. Time-varying correlations for oil – money supply model

The general pattern of the graph of conditional correlations of money supply to oil mimics that of raw data on money supply. For more than 90% of the time under study, the coefficients ranged from 0.5 to 0.85, indicating fairly strong positive correlation. The highest recorded correlation was in 2015. There was a drop in the period from the end of 1998 to the middle of 2000, as per the results in Figure 8.

Correlations dropped to -0.25 in 2002, and this was the only episode of an inverse relationship, as shown in Figure 9. For about 60% of the time under study, the time-varying coefficients ranged from 0.2 to 0.7, which indicates a moderate direct relationship.



Source: calculated by the authors.

Figure 9. Time-varying correlations for oil – exchange rate model

DCC-GARCH food model. Table 6 contains the p-values of the food model.

Table 6. DCC-GARCH food model

	Output (y)	*Inflation (p)*	*Money supply (m)*	*Interest rates (i)*	*Exchange rate (e)*
dcca1 (short-run)	0.033	0.998	0.010	0.999	0.000
dccb1 (long-run)	0.000	0.000	0.000	0.000	0.000

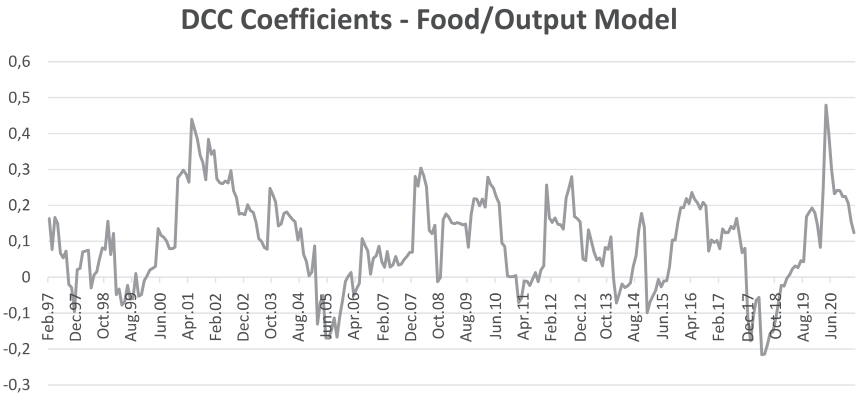
Source: calculated by the authors.

According to Table 6, only long-run spillover effects are significant for all macroeconomic variables. Inflation and interest rates do not exhibit short-term spillover effects, as in the oil model. However, output has significant short-term transmissions here, unlike the oil model. Figure 9 shows dynamic correlations for output with a cap of 0.15 and six significant peaks.

Correlations for interest rates are below zero and within the -0.008 and -0.007 range, which indicates that there is no interdependence between the two economies. Coefficients from inflation lie between 0.13 and 0.14, thereby presenting a low risk of interdependence, as shown in Figure 10.

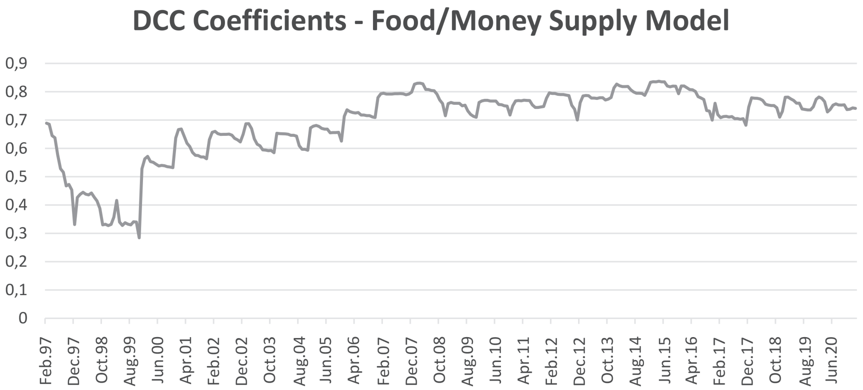
Confirming the oil model, Figure 11 shows that correlations for foreign exchange are positive in the range from 0.6 to 0.85 for 80% of the time under study. There are slight upward peaks in 2007–2008 and 2015 and a pronounced decline from the end of 1998 to mid-1999 within the 0.28-0.4 range.

As presented in Figure 12, dynamic correlations were in the positive region with two major peaks in 2008, 2012 and 2020. However, there was an inverse relationship between mid-2002 and the end of 2003.



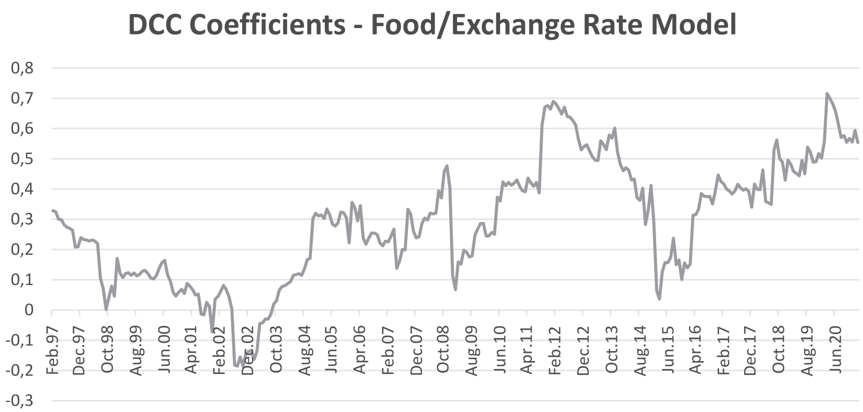
Source: calculated by the authors.

Figure 10. Time-varying correlations for food – output model



Source: calculated by the authors.

Figure 11. Time-varying correlations for food – money supply model



Source: calculated by the authors.

Figure 12. Time-varying correlations for food — exchange rate model

4. Interpretation and discussion of the results

The study uses time-varying correlations in the quest to capture the effect of oil and food price shocks on the interdependence of Brazil and Russia. The GARCH models for oil and food were compared to the DCC-GARCH models to reveal the extent to which the correlations of the macroeconomic variables responded during periods of high volatility.

4.1. Reaction to oil price shocks

It was shown that the periods of highest volatility in world oil prices were the 2008–2009 global financial crisis, the commodity crisis of 2014, and the advent of the Covid-19 pandemic in early 2020 (see Figure 1). Dynamic correlations of the output model concurred with oil volatility only in the third episode. Although higher positive correlations were observed in 2008–2009, the coefficients were much lower than those recorded only in early 2008. Furthermore, the correlations realized in 2014 were actually lower than those in mid-2001. Since Brazil and Russia are major producers of oil, it was expected that the correlations for output would mimic the volatility of oil prices. Leduc and Sill (2004) corroborated this result for Russia, crediting it to the policy of price stability.

Inflation and interest rates yielded almost constant correlations, which did not suggest that there was a relationship between these variables and oil-related innovations. The case for inflation is explained by the price stability mechanisms employed by the Russian central bank. Kilic and Cankaya (2020) found contradictory results in relation to the Russian interest rates, reporting a significant interest rate innovation from oil price shocks. However, Ben Lalouna and Pearlman (2018) found that Brazilian interest rates were robust, not responding to oil innovations, and attributed this phenomenon to relatively high interest rates since 1980.

Correlations for the money supply model do not seem to have any relationship with the oil volatility model. Since the money supply is controlled by the monetary authorities of both countries, this is mostly explained by local rather than international factors. It is for this reason that most scholars preclude the money supply from their studies (Kilic & Cankaya, 2020; Ben Lalouna & Pearlman, 2018).

As in the output model, dynamic correlation coefficients for exchange rates declined rather than increased in 2014 during the commodity crisis. This is a favorable observation from an investment management perspective because it proves that a commodity crisis does not amplify their interdependence. Likewise, correlations were relatively lower than expected during the global financial crisis of 2008–2009. In contrast to the output model, correlations in the exchange rate model rose to their highest peak in early 2020, as did oil volatility. The second highest peak was recorded in the period from mid-2011 to early 2012, which coincided with a moderately tranquil period for oil prices. The Russian central bank has adopted an exchange rate stability regime allowing for intermittent floating of the Ruble in exceptional cases (The Central Bank of the Russian Federation, 2021). This directly impacts the behavior of time-varying correlations and renders them unlikely to track the world oil price volatility.

If the three crises that affected oil price volatility could be compared in terms of financial severity, the Covid-19 pandemic would be the most serious. The results show that oil innovations compounded positive correlations during that time and would probably foster contagion under similarly stressful conditions.

4.2. DCC-GARCH – Food

Dynamic conditional correlations were computed for paired economic indicators for comparison with the food price volatilities (see Figure 2). There was significant volatility in world food prices during the 2008–2009 global financial crises. However, relative tranquility was observed throughout the rest of the time under study, even during the Covid-19 pandemic. Output correlations rose sharply in early 2020 in response to the pandemic, like in the oil model. The second highest positive correlation was observed in 2001. Surprisingly, low correlations in 2008–2009 are sandwiched by periods of higher correlations. This puzzle is analogous to the one in the oil model and represents a positive development for international investors.

With seemingly stable correlation coefficients throughout the period of study, inflation and interest rate variables did not respond to international food price shocks. The observed near-zero correlations point to no association between the interdependence of Brazil and Russia and food innovations.

Interestingly, the money supply returned a similar pattern of time-varying correlation coefficients to the oil model. This behavior could be attributed to the level of control imposed by the monetary authorities. Correlations plunged slightly during 2008–2009, yet their fall cannot be directly linked to international food prices.

In the exchange rate model, the highest peaks of correlations were noted in early 2020 and 2012 when food prices were relatively stable. In contrast, there was a dramatic fall in the coefficients in 2008 when food prices were experiencing the highest volatility.

The concept of matching food price volatility with dynamic correlations in order to identify episodes of convergence is innovative. While the SVAR food output was comparable to other studies, the results of the DCC-GARCH could not be compared with other empirical literature.

Conclusions

Overall, more peaks of time-varying correlations in the oil model may be attributed to oil price volatility rather than to food price volatility in the food model. However, the results show that Brazil and Russia have long-run spillover effects on all macroeconomic variables in response to both oil and food price shocks. This finding is comparable to that of Li and Guo (2021), who found that oil price volatilities were a statistically significant determinant of spillover effects among the BRICS economies in general. Furthermore, the money supply and exchange rate variables exhibited short-run effects with high positive dynamic correlations. The interdependence of output and exchange rate variables defied the global financial crisis of 2008–2009 and the commodity crisis of 2014 but rose significantly during the Covid-19 health crisis. This mollifies investors' concerns during financial and commodity crises but leaves them exposed to other global crises of greater reach and severity. Similarly, food price volatility coincided with a drop in correlations for output and exchange rates variables. The money supply exhibited a unique pattern that could not be directly linked to oil and food price volatility. Interest rates and inflation had constant dynamic correlations that did not respond to innovations related to oil or food. A prudent investor will strive to attain a diversified portfolio of the BRICS countries and some other blocs or large economies that are major importers of oil and food produce.

Of all the variables under study, the money supply produced strong positive correlations before and after the formation of the BRICS. Further studies could investigate this phenomenon because it influences spillover effects both in the short run and more so in the long run. The fact that the DCC-GARCH results showed more peaks than the oil and food price volatility graphs suggests that there are stronger explanatory variables that need to be studied. For example, studies could seek to unearth what happened in 2001–2002, 2011–2012 and 2017–2018 that led to spikes in positive dynamic correlations. Once the appropriate variables are identified, causality studies could also be explored. Such studies should pay attention to regime changes, preferably using spectral causality, in order to estimate the dynamic aspects of causality over time.

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